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EEG Signal for Diagnosing Diseases using Machine Learning

Aswathy K J[1], Swathi Anil[2], Prof. Elizebath Issac[3]
[1,2,3] Department of Computer Science and Engineering, Mar Athanasius College of Engineering, Kothamangalam, India

ABSTRACT

Alzheimer's disease is a chronic neurodegenerative disease that usually starts slowly and worsens over time. Alzheimer's is an irreversible, progressive brain disorder that slowly destroys memory and thinking skills, and eventually the ability to carry out the simplest tasks. In most people, symptom first appears in their mid-60s. Studies have reported that electroencephalogram (EEG) signals of Alzheimer's disease patients usually have less synchronization when compare to healthy people. Changes in EEG signals start at early stage but, clinically, these changes are not easily detected. Early detection of Alzheimer's can have treatments with more positive outcomes. The aim of this paper is to classify Alzheimer's disease patients using EEG signal processing in order to support medical doctors in the right diagnosis formulation. The proposed system consists of mainly five steps: Signal Acquisition, Pre-processing, Feature Extraction, Feature Selection, and Classification. The Signal Acquisition makes use of EEG dataset, Band-pass-filtering is used in the pre-processing stage to get artifact free signal. The necessary features are then extracted from EEG signals using Wavelet Transform and they are subjected to Principal Component Analysis (PCA) for feature selection. The classification is done using Block Based Neural Network (BBNN). Based on the changes in EEG the structure and internal configuration of BBNN are modified.
Keywords : Alzheimer's disease (AD),EEG, Principal Component Analysis, BlockBased Neural Network.

I. INTRODUCTION

Alzheimer's disease (AD) is a neuro-degenerative disease, the most common form of dementia, third most expensive disease and sixth leading cause of death in the United States. It affects more than 10% of Americans over age 65, nearly 50% of people older than 85, and it is estimated that the prevalence of the disease will triple within the next 50 years. While no known cure exists for Alzheimer's disease, a number of medications are believed to delay the symptoms (and perhaps causes) of the disease.The most popular 10 warning signs of Alzheimer's disease as: Memory loss, Difficulty performing,Problems with language, Poor or decreased judgment, Problems with abstract thinking, Misplacing things, Changes in mood, or behavior, Changes in personality, Loss of initiative.

The progression of the disease can be categorized in four different stages. The first stage is known as Mild Cognitive Impairment (MCI), and corresponds to a variety of symptoms — most commonly memory loss — which do not significantly alter daily life. Between 6 and 25% of people affected with MCI progress to AD every year. The next stages of Alzheimer's disease (Mild and Moderate AD) are characterized by increasing cognitive deficits, and decreasing independence, culminating in the patient's complete dependence on caregivers and a complete deterioration of personality (Severe AD) .

Diagnosis of MCI and AD is important for several reasons such as: A positive diagnostic gives the patient and his family time to inform them- selves about the disease, to make life and financial decisions related to the disease, and to plan for the future needs and care of the patients. A negative diagnostic may ease anxiety over memory loss associated with aging. It also allows for early treatments of reversible conditions with similar symptoms (such as thyroidal problems, depression, and nutrition or medication problems).Current symptoms-delaying medications have a given time frame during which they are effective. Early diagnosis of AD helps ensure prescription of these medications when they are most useful. Early diagnosis of AD also allows prompt treatment of psychiatric symptoms such as depression or psychosis, and as such reduces the personal and societal costs of the disease. As research progresses, preventive therapies may be developed. Early diagnosis raises the chance of treating the disease at a nascent stage, before the patient suffers permanent brain damage. Finally, as institutionalization accounts for a large part of health care costs incurred because of AD, by preserving patients' independence longer and preparing families for the needs of AD patients, timely diagnosis further decreases the societal costof the disease. Medical diagnosis of Alzheimer's disease is hard, and symptoms are often dismissed as normal consequences of aging. Diagnosis is usually performed through a combination of extensive testing and eliminations of other possible causes.

Psychological tests such as Mini Mental State Examinations (MMSE), blood tests, spinal fluid, neurological examination, and increasingly, imaging techniques are used to help diagnose the disease databases because of their high computational cost. However, their use is often limited to numeric data.

A traditional method of identifying Alzheimer is visual analysis of the EEG recordings by the trained professionals. It is very costly as well as tedious task to review a 24-h continuous EEG recording, particularly if there are large number of EEG channels to review. Moreover, the detection of Alzheimer by visual scanning of a patient's EEG data is a tedious and time consuming process. In addition, to detect Alzheimer's an expert is required to analyse the entire length of the EEG recordings [5]. Automatic detection is preferred, as complete visual analysis of EEG signal is very difficult. A reliable automatic classification and detection system will ensure that the objectives are met and will facilitate treatment and significantly improve the diagnosis of Alzheimer.

Automating the detection of Alzheimer is very important for assisting neurologists to analyse the EEG recordings. It could also offer solutions for closed-loop therapeutic devices such as implantable electrical stimulation systems. The long-term treatment with anti-Alzheimer drugs, may cause cognitive or other neurological side effects, this could be reduced to a targeted short-acting intervention. Therefore, the development of such automated systems is highly demandable, due to the huge amounts and the increased usage of long-term EEG recordings for proper evaluation and treatment of neurological diseases, including Alzheimer. The failure due to the expert misreading the data and lack of making proper decision would also be narrowed down. There are five stages in the automated diagnosis of Alzheimer such as, signal acquisition, pre-processing, feature extraction, and classification.

The objective of the proposed system is to develop a new method for automatic detection and classification of EEG patterns into three categories MD or Alzheimer's using a Block Based Neural Network (BBNN) and wavelet feature extraction method. The BBNN parameters are optimized using Particle Swarm Optimization (PSO) algorithm.

II. LITERATURE SURVEY

Many automatic Alzheimer detection techniques using machine learning approach are been in UE since 1980s. Among these techniques the areas listed below are prominent areas of research undergoing presently in order to provide more sophisticated and better results.

The EEG was developed as a manse to investigate the mental processes. The brains electrical activity was first recorded and reported by Caton in 1875 in exposed brains of rabbits and monkeys. In 1929, the first measurement of brain electrical activity in humans was reported by Hans Berge. Since then, the EEG signal has been utilized clinically to evaluate neuron's behaviour and functional states of the brain such as (a) different stages of wakefulness (b) sleep or (c) metabolic disturbances.

EEG is an electrophysiological monitoring method which is used to record electrical activity of the brain. EEG measures voltage fluctuations which is caused due to ionic current within the neurons of the brain. EEG refers to the recording of the brain's spontaneous electrical activity over a period of time,[1] as recorded from multiple electrodes placed on the scalp. EEG is most often used to diagnose epilepsy, which causes abnormalities in EEG readings. It can also be used to diagnose sleep disorders, coma, encephalopathy, and brain death. It is measured with electrodes which are placed on standard positions on the head. In clinical and research applications, the name and location of these electrodes are specified by the international standard 10/20 system. This system relies on the relationship between the location of an electrode and the underlying area of cerebral cortex. The '10' and '20' represents the actual distances between adjacent electrodes which is either 10% or 20% of the total front-back or right-left distance of the skull. The range of amplitude for an EEG signal is 5 to 200 µV and frequency ranges from 1 to 30 Hz.

In 2009, Martis*et.al* proposed a novel feature extraction scheme on electrocardiogram (ECG) signal using discrete wavelet transform (DWT)In this research, the discrete wavelet transform (DWT) based on dyadic (powers of 2) scales and positions, was used to make the algorithm computationally very efficient without compromising accuracy. The EEG was subjected to a level 4 decomposition using fourth-order Daubechies wavelet transform.

A data selection algorithm depending on phase congruency to determine Alzheimer from the background EEG was proposed by Logesparan& Rodriguez-Villegas in 2011. The phase congruency denoising was performed by dynamic estimation and compensation for muscle activity in EEG. The approach involved the modification of traditional phase congruency to include the dynamic estimate of muscle activity in the input scalp EEG signal. The authors report that the performance of the data selection algorithm was enhanced to 80% sensitivity for more than 50% data reduction.

Yusof*et.al* proposed a new mutation operation for rapid feature selection by GA. The fittest chromosomes were preserved by normal elitism in GA, which were then evaluated by utilizing the fitness function. The highest fit allele was conserved and the evaluation of fitness of the allele performed based on the frequency of the occurrences. The chromosome that underwent this mutation approach was found to have the highest fitness as it was created based on the fittest alleles.

Akhtar*et.al* [19] have proposed a framework based on Independent Component Analysis (ICA) and Wavelet Denoising to enhance the pre-processing of EEG signals. The Spatially Constrained ICA (SCICA) was used for extracting artifact-only Independent Components (ICs) from the EEG data. The cerebral activity from the acquired artifacts ICs was removed by using WD. The subtractions of the artifacts from the EEG signals were then performed to get clean EEG data. The main benefit of the approach was reported to be the speedy computation as there is no need for identifying all ICs. The approach also achieves effective removal of focal artifacts which can be well separated by SCICA.

In 2007, Lucia *et.al* proposed a novel feature extraction scheme for automated classification of Alzheimer in the human electroence
phalogram-based on principal component analysis.
In 2009, Martis*et.al* proposed a novel feature extraction scheme on electrocardiogram (ECG) signal using discrete wavelet transform (DWT) coefficients followed by PCA. In the method, the principal components of the sub bands of discrete wavelet transformed signal in the compact supported basis space represent the data better than in the time domain. The method provided better results.

In 2012, Acharya*et.al* proposed the use of principal component analysis for automatic classification of Alzheimer EEG activities in wavelet framework. PCA was used for feature selection and it yielded 97% classification accuracy.

The objective of classification is to describe a boundary between the classes and to label them based on their measured features. Guo*et.al* [20] have presented a novel method of automatic Alzheimer detection. This new approach used entropy features derived from Multi Wavelet Transform (MWT), which was then combined with an Artificial Neural network to classify the EEG signals about the presence of Alzheimer. The authors reported that Multi-wavelets achieved better results than scalar wavelets. However, they also place on record that Multi-wavelets produce more number of sub-signals which increase the computational cost. The raw EEG data are decomposed into sub-signals through Multi Wavelet Transform. The formation of feature vector is performed by extracting Approximate Entropy (ApEn) for each sub-signal.

Moon *et.al* in 2001, proposed a novel block based neural network (BBNN) model and the optimization of its structure and weights based on genetic algorithm. The optimized BBNN could solve the engineering problems such as pattern classification and mobile robot control.

In 2007, Jiang *et.al* proposed a novel BBNN model with block wise least squares learning algorithm (BLS). The optimal internal weights of BBNN are found using this BLS algorithm. The method improved the convergence speed with orders of magnitude.

Later in early 2016, BBNN model along with particle swarm optimization algorithm used for optimizing the internal structure of BBNN was proposed by Shadmand*et.al* for classification of Personalized ECG signals. The performance evaluation results show a high classification accuracy of 97%.

III. PROPOSED SYSTEM

A novel technique for the automated analysis of EEG signal is proposed and investigated for classifying the signal as normal or Alzheimer. This method is based on classification of EEG signals using BBNN in which the features are extracted using wavelet transform method. The parameters of neural network are optimized using the Particle Swarm Optimization (PSO) algorithm. This method is proposed in order to eliminate the difficulties and limitations involved in using visual inspection for analyzing the EEG signal.

The proposed method is automatic. Hence it is not subjective and thereby eliminates the need for the visual inspection based method which is subjective. Moreover, the performance of the proposed method is better as compared to the existing visual inspection based method of EEG signal classification. Figure 1 shows the basic architecture of the proposed method.

Figure 1. Basic Architecture

An EEG signal is first analyzed and fed to the classifier. The input signal received by the classifier, uses it for classifying depending on the input signals received during the training phase. Proposed system uses a novel classification method which uses the BBNN and the parameters are optimized using PSO.

The proposed system consist of five stages and they are – Signal Acquisition, Pre-processing, Feature Extraction, Feature Selection and Classification. The proposed architecture is as shown in Figure 2. It shows the relationship between each phase with its predecessor phases.

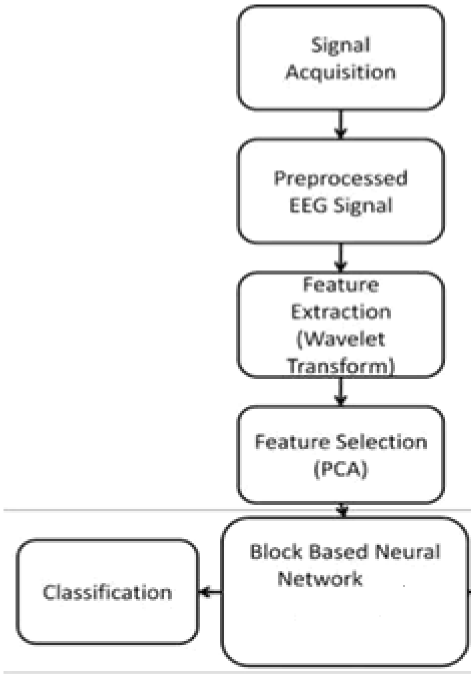

Figure 2. Proposed system architecture

The work addresses the problem of classifying EEG signal as either normal or Alzheimer's. In the Signal Acquisition phase, only two subsets (set A and set E) from the dataset which was available online are made use of. In Signal Acquisition phase, the EEG segments are filtered by a low pass filter of cut off frequency 40 Hz and a stop band frequency of 50Hz to remove the artifacts from them Both these phases together constitutes the input module.

After obtaining artifact free signals in the preprocessing phase, necessary features are then extracted from EEG signals using Wavelet Transform. The EEG signals thus obtained undergo wavelet decomposition with five scales using db4 wavelet. Among all the wavelets forms db4 wavelet is selected because of its smoothing feature that makes it appropriate for detecting changes in EEG signals. With the use of feature Selection the dimensions of feature vectors are reduced. In the proposed work, the significant sub-bands are subjected to PCA for feature selection. Two principal components are considered from each of these sub-bands and are taken as effective features. These two phases thus together constitute the feature processing module.

The next phase is the Classification phase. For this a BBNN is made use. The features thus selected are then sent to a BBNN for classification. In this work, BBNN is used as a multi class problem. Half the data from each set are selected for training the BBNN while the rest are used for testing. The parameters of BBNN are optimized using a PSO algorithm. The output module is obtained at the classification phase.

The test performance of the proposed method is evaluated. And it is defined **by** four performance parameters such as: sensitivity, specificity, classification accuracy and positive predictive value. Sensitivity defines the ratio of the number of correctly detected positive patterns to the total number of actual positive patterns. A positive pattern indicates that Alzheimer is detected. Specificity is specified as the ratio of the number of correctly detected negative patterns to the total number of actual negative patterns. A negative pattern indicates a detected non Alzheimer's. The total classification accuracy is defined as the ratio of number of correctly classified patterns to the total number of patterns. Positive predictive is given as the ratio of the number of correctly detected positive patterns to the sum of true positives and false positives.

IV. CONCLUSION

Accurate automated Alzheimer detection remains an important challenge and a critical first step in removing the uncertainty associated with when Alzheimer will occur and furthering the understanding of Alzheimer and its causes. In the proposed method, the EEG signals have been classified in five classes. A classification system for this purpose makes use of a Block Based Neural Network (BBNN) with Particle Swarm Optimization (PSO) for optimization of parameters. BBNN addresses a multi class problem. BBNN has been trained with a training dataset and tested using a test data set. Each of these data sets contains a number of EEG records of data set. The features which are extracted from EEG signals have been used as BBNN inputs. Particle Swarm Optimization method is used as BBNN training algorithm and also to optimize the BBNN structure and the weights. The BBNN trained with PSO algorithm presents a high quality system for EEG signals classification. In the proposed method, signal preprocessing signal acquisition phase, preprocessing phase, feature processing which consisting of the feature extraction and feature selection phases and classification module consisting classification of EEG signals using BBNN and the parameters are optimized using PSO algorithm.

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